Acta Tropica 163 (2016) 90–97

Contents lists available at ScienceDirect

Acta Tropica

journal homepage: www.elsevier.com/locate/actatropica

# Cutaneous leishmaniasis prevalence and morbidity based on environmental factors in Ilam, Iran: Spatial analysis and land use regression models

Mehdi Mokhtari[a], Mohammad Miri[b], Ali Nikoonahad[a,c,*], Ali Jalilian[c], Razi Naserifar[d], Hamid Reza Ghaffari[e,f], Farogh Kazembeigi[c]

[a] Department of Environmental Health Engineering, School of Health, Shahid Sadoughi University of Medical Sciences, Yazd, Iran
[b] Department of Environmental Health Engineering, School of Public Health, Sabzevar University of Medical Sciences, Sabzevar, Iran
[c] Department of Environmental Health Engineering, School of Health, Ilam University of Medical Sciences, Ilam, Iran
[d] Vice-Chancellor for Health, Ilam University of Medical Science, Ilam, Iran
[e] Social Determinants in Health Promotion Research Center, Hormozgan University of Medical Sciences, Bandar Abbas, Iran
[f] Department of Environmental Health Engineering, School of Public Health, Tehran University of Medical Sciences, Tehran, Iran

A R T I C L E  I N F O

*Article history:*
Received 31 December 2015
Received in revised form 9 July 2016
Accepted 2 August 2016
Available online 3 August 2016

*Keywords:*
Cutaneous leishmaniasis
Spatial analysis
Environmental variable
LUR
GIS

A B S T R A C T

The aim of this study was to investigate the impact of the environmental factors on cutaneous leishmaniasis (CL) prevalence and morbidity in Ilam province, western Iran, as a known endemic area for this disease. Accurate locations of 3237 CL patients diagnosed from 2013 to 2015, their demographic information, and data of 17 potentially predictive environmental variables (PPEVs) were prepared to be used in Geographic Information System (GIS) and Land-Use Regression (LUR) analysis. The prevalence, risk, and predictive risk maps were provided using Inverse Distance Weighting (IDW) model in GIS software. Regression analysis was used to determine how environmental variables affect on CL prevalence. All maps and regression models were developed based on the annual and three-year average of the CL prevalence. The results showed that there was statistically significant relationship ($P$ value $\leq 0.05$) between CL prevalence and 11 (64%) PPEVs which were elevation, population, rainfall, temperature, urban land use, poorland, dry farming, inceptisol and aridisol soils, and forest and irrigated lands. The highest probability of the CL prevalence was predicted in the west of the study area and frontier with Iraq. An inverse relationship was found between CL prevalence and environmental factors, including elevation, covering soil, rainfall, agricultural irrigation, and elevation while this relation was positive for temperature, urban land use, and population density. Environmental factors were found to be an important predictive variables for CL prevalence and should be considered in management strategies for CL control.


## 1. Introduction

Cutaneous leishmaniasis (CL) is a zoonotic disease with rodents as the reservoirs and female phlebotomine sand fly as a vector. Approximately 90% of the total Leishmaniasis occur in eight countries of the world, including Iran (Doudi, 2011). In Iran, Leishmaniasis is mostly found as the zoonotic CL type (Salah et al., 2007). Leishmaniasis is a multi-reservoir disease and due to the reservoirs dependency on the environmental conditions, the distribution of the disease can be associated with the environmental factors such as temperature, humidity, rainfall, and land use (Ali-Akbarpour et al., 2012; Cortes et al., 2012; Salah et al., 2007).

According to the statistical analyses, the distribution of CL has shown a negative correlation with relative humidity and a positive correlation with annual rainfall (Salah et al., 2007; Salahi-Moghaddam et al., 2015).

GIS and regression models have been widely used in CL studies. In France, Land-Use Regression (LUR) method was applied to assess the impact of the environmental conditions on the distribution of CL in areas with a Mediterranean climate in order to predict the probability of CL incidence in selected areas and to create a predictive risk map of CL prevalence using Geographic Information System (GIS) (Chamaillé et al., 2010). In India, predictive risk map generated by GIS revealed that the density of sand flies infected with Leishmania was higher in areas around the swamps and near the rooted

* Corresponding author at: Department of Environmental Health Engineering, School of Health, Shahid Sadoughi University of Medical Sciences, Yazd, Iran.
*E-mail address:* nikoonahad_ali_n@yahoo.com (A. Nikoonahad).

http://dx.doi.org/10.1016/j.actatropica.2016.08.002
0001-706X/

trees and sugarcane plantation (Bhunia et al., 2012; Sudhakar et al., 2006).

The most popular model in GIS is IDW by which spatial distribution of the disease can be provided. In the IDW method, the weights of the data are inverse function of the distance between data points. An exponent of the distance has to take values greater than zero. For instance, a value of 2 would mean that the data are inversely weighted as the square of the distance (Gumiere et al., 2014; Webster and Oliver, 2007). The IDW method is deterministic and shows no discontinuities when the weighting exponent is greater than zero. However, weighting exponent selecting is somewhat arbitrary and the IDW method does not take into account the configuration of the sampling scheme (Webster and Oliver, 2007). IDW method has been widely used to determine the spatial distribution of LC and other diseases (Bhunia et al., 2013; das Chagas Xavier et al., 2012; Hanafi-Bojd et al., 2012; Ryan et al., 2006; Shirzadi et al., 2015).

Simultaneous use of the regression models and GIS can be critical for CL control by which the spatial distribution are determined and the risk prone areas to be infected in the future are predicted (Bavia et al., 2005). According to various published information regarding sand flies, a digital database providing and transmission modeling and predicting across the countries can help the health authorities to make more correct and prompt decisions in planning for leishmaniasis control (Karimi et al., 2014).

LUR is a combination of GIS and regression analysis in which raw data are firstly prepared by statistical methods and then used in GIS to create the spatial map. LUR model provides useful local information about the distribution of the diseases and environmental pollutants for the users and decision makers (Chamaillé et al., 2010; Salahi-Moghaddam et al., 2015). This model can be developed based on the meteorological and environmental factors such as temperature, wind direction, rainfall, and land use type (Bhunia et al., 2013; Hoek et al., 2008; Liu et al., 2015).

Therefore, with respect the above, this study was aimed to cover the followings:

- Investigation of CL prevalence and morbidity in the study area and spatial analysis of CL prevalence based on IDW method.
- Investigation of the role and proportion of PPEVs in the distribution and prevalence of CL disease in the study area.
- Developing a LUR model in the study area by which the impact of the PPEVs on disease distribution is determined and the risk map of disease at present and in the future is created.

The results of the present study can be used to determine the proportion of environmental factors on CL transmission. This may facilitate the interventions in CL control which has shown an increasing growth in recent years. Also the predictive risk map of the prevalence may help to select the low risk areas for the development of new cities, villages, and habitations and settlement of military and non-military camps in the frontier and remote regions.

## 2. Materials and methods

### 2.1. Study area

Ilam province is located in western Iran with a population of about 557,599 and a total surface area of 20133 km$^2$. It is situated between 45°24′ and 48°10′ longitude, and 31°58′ and 34°15′ latitude sharing a land border with Iraq. This province is recognized as one of the endemic areas of CL in the Middle East (Nejati et al., 2014). Fig. 1 shows the location of this province in Iran and the Middle East. The climate varies from cold semi-humid in the north to hot desert in the south of the province. Average annual rainfall is 520 mm in northern areas and 150 mm in southern areas. In northern areas, mainly in the mountains, lands are covered by semi-forest (Oak forest), while the southern areas are mainly desert and semi-desert. Around the villages, there are mostly barren land, dry farming, and irrigation lands (Arekhi et al., 2010). Topsoil is predominantly covered with gypsum, limestone, clay, or a combination of them (Ali-Akbarpour et al., 2012). The province was considered as a war area for eight years after Iraq attack on Iran in 1981. Lack of appropriate health services during the war years, displacement of Iran and Iraq military forces, and the environmental conditions along with other related factors have accelerated the prevalence of some contagious diseases such as CL in this area (Nejati et al., 2014).

### 2.2. Collection and preparation of leishmaniasis data

The statistical information and exact postal addresses of CL patients who had referred to 64 health centers (as is illustrated in Fig. 1) from 2013 to 2015 were collected. Since the signs of CL develop almost two months after sand fly bite (Ali-Akbarpour et al., 2012; Salahi-Moghaddam et al., 2015; Yoosefi and Vakil, 2007); therefore, the time of the biting was used in data analysis in order to assess the role of the environmental variables on disease. Based on the postal addresses, accurate geometric locations of patients were specified in terms of latitude and longitude at the Universal Transverse Mercator system. A mobile GPS device (eTrex 20 Garmin, USA) was used for recording the Latitude (Y) and Longitude (X) of the locations. The accurate locations of 3237 CL patients were prepared to be used in GIS. CL data were also generated to be applied in LUR examinations for determining the annual and the three-year average morbidities.

### 2.3. Generation of spatial predictors

In this study the environmental variables affecting the prevalence of CL were recognized and after separation of the areas according to the type of the effective variables, the association between each variable and the prevalence of CL was determined using GIS. Regression equations were generated between the sorted variables and the prevalence of CL. These equations which were derived from the current status of the infected areas were used to map the risk of prevalence in other spots. For this purpose, with regard to previous studies (Ali-Akbarpour et al., 2012; Chamaillé et al., 2010; Chaves and Pascual, 2006; Desjeux, 2001; Elnaiem et al., 2003; King et al., 2004; Reithinger et al., 2007; Salah et al., 2007; Sudhakar et al., 2006; Weigle et al., 1993), 17 PPEVs in six classes with probable impact on CL prevalence were investigated (Table 1). The six classes included temperature, rainfall, population, type of soil (3 variables), land use (6 variables), and elevation. Considering the flight range of the sand fly as the vector of the disease as well as the motion range of the rat as the main reservoir of CL, two buffer zones were drawn with radii of 500 (the highest influence) and 1000 m (the least influence) around the prevalence area for nine predictive variables whose their types and amounts were expected to be changed in distances more than 500 m (Table 1). Previous studies had reported the activity distance of sand flies and rats from 500 to 1000 m (Nejati et al., 2014; Yoosefi and Vakil, 2007). For three PPEVs of temperature, rainfall, and elevation which did not change much with low distance, altitude lines of isotherm, isohyet, and isohypse were used instead of radial area. The digital data of the present study were the vector type taken from related organizations. Temperature and precipitation data were provided based on an annual mean precipitation map prepared by the province Meteorological Organization. The population density of each region was based on the population maps provided by the Ilam Governor. Soil type map, DEM layer, and land use map were taken from the

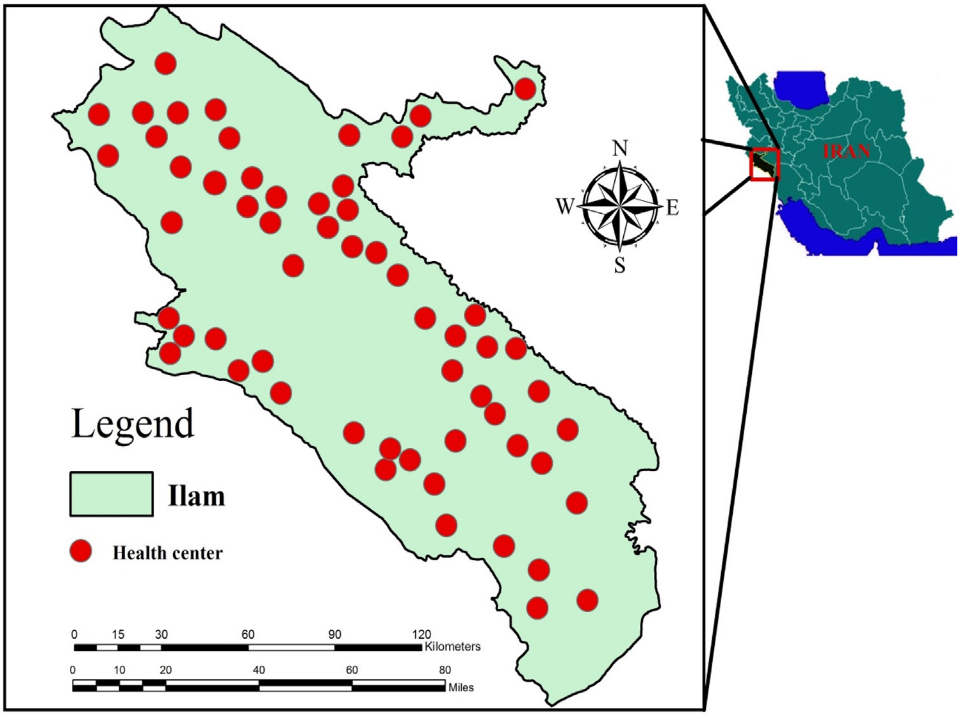


**Fig. 1.** Ilam province location in Iran and the Middle East, and location of health centers(red spot) where the leishmaniasis data were derived. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 1**
Classes and potentially predictive environmental variables (PPEVs) in distribution of CL.

| Class | Description | Variables predictor | Buffer radii (m) |
|---|---|---|---|
| Population | Density population (persons per km$^2$) | Density of population | 1000 |
| Elevation | Altitude above sea level | 100–400 m 400 m< | 1000 |
| Land use | Type of land use | Dry Farming Irrigated agriculture Urban Forest Poor land | 500 and 1000 500 and 1000 500 and 1000 500 and 1000 500 and 1000 |
| Type of soils[a] | Surface soils | Inceptisols[b] Bad Lands Aridisols[c] | 500 and 1000 500 and 1000 500 and 1000 |
| rainfall | Average annual precipitation (mm) | 100–300 300–500 500< | – |
| Temperature | Average annual temperature (°C) | <30 30–40 40< | – |

[a] Surface soils.
[b] Inceptisol soils are more developed than Entisols soils, but these soils are at the early stages of soil profile development.
[c] Aridisol soils (or desert soils) have a very low concentration of organic matters.

Ilam province Geology Center. Temperature and precipitation maps were in the form of isotherm and isohyet lines, which were entered into the GIS software and converted to raster files with horizontal resolution of 5 × 5 m.

## 2.4. Regression analysis

Considering the discrete data, Poisson regression was used to develop the LUR model. In studies conducted in Tunisia and Southern and Eastern Mediterranean, correlated Poisson distribution was applied to examine the correlation between the prevalence of the visceral leishmaniasis and climate parameters (Ben-Ahmed et al., 2009; Salah et al., 2007). With regard to the studies on estimating the distribution of diseases and environmental pollutants (Amini et al., 2014; Hoek et al., 2008; Liu et al., 2015; Sabaliauskas et al., 2015; Wasserberg et al., 2003), significance level of 0.05 was considered as inclusion and exclusion criteria of PPEVs in Poisson regression model. Independent variables with p-value > 0.05 were excluded from the regression model. To measure the validity of the model and to avoid wrong estimation, *P* value, RMSE (Root Mean Square Error), %RMSE, and $R^2$ coefficient were used.

Poisson regression is used to predict countable dependent variables. When the frequency of the independent variable is low for modeling process or observed data have the frequency of zero, natural logarithm models are unable to appropriately predict the dependent variable. The main reason for this is the assumption of normal distribution considered for data. In this condition, Poisson regression can be used which models the incidence of discrete and rare events. Also correlated Poisson distribution is a probable discrete distribution for describing of an accident occurrence probability for a certain number of times and in fixed interval or distance. General equation of regression is as follows:

$$f(k;\lambda) = \frac{\lambda^k e^{-\lambda}}{k!},$$

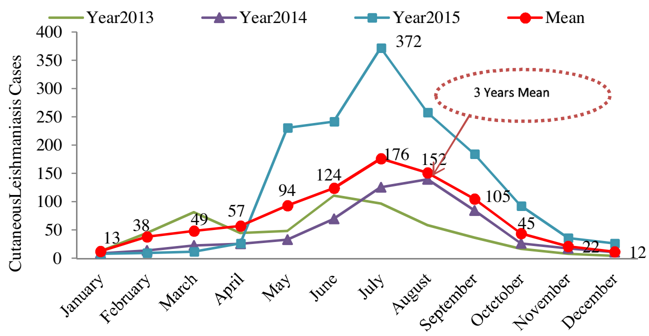


**Fig. 2.** Three-year average and monthly changes of CL from 2013 to 2015 in Ilam province, Iran.

Where *e* is the Neperian logarithm, *k* is the number of an accident occurrences, and $\lambda$ is a positive real number which is equal to the mathematical expectation of occurrences in a given interval.

### 2.5. Distribution and predictive risk map

In this study, the distribution and predictive risk map of the disease were generated using ArcGIS software (version10.1). The Distribution of the disease was mapped using Inverse Distance Weighting (IDW) model in which the longitude and latitude of the postal addresses were applied without considering the environmental variables. In this model, various tendencies of the density in the area were derived using interpolated method and illustrated as a different color continuum. The source of the data to generate LUR map was an environmental variables layer (such as DEM, land use, soil type, and rainfall) prepared in raster format. The Raster Calculator of the ArcGIS Spatial Analyst extension was used to render final regression equations into predictive risk map in order to estimate the CL prevalence based on the three-year average of the disease density in the study region. Generated raster files from vector data were adjusted in a way that the cells out of the buffer zones were given the zero and the intra-buffer cells received the highest value.

## 3. Results

### 3.1. Prevalence data

Monthly and annual changes of CL prevalence were shown in Fig. 2. Monthly changes revealed that, in all the years, morbidity rate began to be increased in April and May when the warmth started to be increased and reached the maximum values in July and August while with the beginning of coldness in autumn, morbidity rate decreased. The lowest monthly morbidity rate on the basis of the 3-year average was recorded for the coldest months of December and January with 13 and 12 cases, respectively, while the highest morbidity rate were observed in July with 176 patients which was one of the warmest months with average daily temperature of 40 °C. CL Prevalence was significantly increased in 2015 when compared with 2013 and 2014 ($P = 0.01$). Field studies showed that in the beginning of 2013, the Province Health Center had performed a broad programs of insecticides spraying, rodents killing and dogs straying to control the disease. This could be the reason why prevalence was lower in 2013. However, as the environmental fight against CL reservoirs was stopped, the prevalence increased in 2014 and intensified in 2015.

### 3.2. Final LUR models

Among the total 17 predictive variables used for LUR, 11 (64%) variables were significantly associated with the prevalence of CL (Table 2), while some of them were defined in 500 and 1000 m radius. The 11 variables which was known as the predictive parameters of the CL prevalence included elevation, population, rainfall, temperature, urban500, urban1000, Inceptisol500, Inceptisols1000, poorland500, dry farming500, dry farming1000, Aridisol soil1000, forest500, and irrigated land500. The impact of these parameters on CL prevalence was significant at least in one of four regression equations which were shown in Table 2. The $R^2$ value of regression equations for 2013, 2014, 2015, and 3-year average were 0.942, 0.890, 0.813 and 0.859, respectively (Fig 5). The p-value was less than 0.001 for all years and conditions except for the 2015 which was less than 0.003. The highest RMSE (14.66) was calculated for 2015 while it was 2.84 for 2014 and 4.15 for 2013. For 3-year average regression equation, %RMSE found to be 19.6. These values imply that the model prediction errors are in an appropriate range (<20). Generally, there were a good consistencies among the investigated years and the 3-year average, particularly in $R^2$ and p-value.

### 3.3. Regression map

The predictive risk and distribution maps of the CL prevalence produced by LUR models were shown in Fig. 4. The model prediction for CL prevalence in the northern, central, and eastern regions of the province was near zero (in red). The highest probability of CL prevalence was predicted in the west and frontier with Iraq (in blue). The regions with the highest probability of CL prevalence or predictive hotspots were observed to be located in the west and southwest of the province around the cities of Mehran and Dehloran. The regression map predicted the annual average of 187 cases per km$^2$ in these cities. According to the prediction models, the various intensities risks of CL prevalence existed in approximately 30% of the investigated regions. The probability of the prevalence gradually decreased from the frontier towards the center of the province.

## 4. Discussion

The statistics information of the patients in three consecutive years beside the digital layers of the environmental geography were used to perform the LUR. Then regression equations were derived from LUR and digital maps of environmental geography and was used to provide the predictive risk map of the CL distribution.

Regression Analysis indicated that there were positive correlation between yearly and 3-year average CL prevalence and regional temperature. The coefficient of temperature in regression equation of 2013 was 0.35 and increased to 0.412 and 0.675 in 2014 and 2015, respectively. the most probable expalntion for these results may be the environmental control actions conducted by the regional health center for prevention of CL prevalence during 2013. Also in 2015, CL prevalence was dramatically increased due to unknown reasons and leaded to slight increase in coefficient of temperature in regression equation. Positive effect of temperature in CL prevalence in regression equations of all the three years and the average was in agreement with Fig. 2 in which the changes of the prevalence were shown according to temperature variations. Both in spatial distribution map (Fig. 3) and predictive risk map (Fig. 4), the highest distribution and risk of prevalence were found in tropical regions of the province. This results are in consitent with the previous study in which a statistically significant relationship between the CL prevalence and increased temperature were reported in dif-

**Table 2**
Final land use regression models for leishmaniasis in average and three consecutive years (2013–2015).

| | Equation | $R^2$ | P value | RMSE[k] | %RMSE |
|---|---|---|---|---|---|
| 3-year average | 8.382 + 1.854E-5P[a] – 0.007R[b] – 0.002EL[c] + 10.752U[d] 500 – 0.796A[e] 500 – 0.111I[f] 1000 + 0.47T[l] | 0.859 | 0.001 | 12.28 | 19.6 |
| Year 2013 | 4.194 + 8.664E-6P – 0.005R – 1.745E-5EL + 11.873U500 – 0.27D[g] 1000 + 0.362PO[h] 1000 + 0.239A1000 + 0.079I1000 + 0.35T | 0.942 | 0.001 | 4.15 | 27.24 |
| Year 2014 | 5.178 + 9.184E-5P – 0.003R – 0.006EL + 4.108U500 – 0.938PO500 + 0.734U1000 – 0.575I500 + 0.412T | 0.890 | 0.001 | 2.84 | 19.48 |
| Year 2015 | 9.16 + 1.34E-5P – 0.004R – 0.008EL – 2.989PO500 + 0.918U1000 – 0.916I500 – 2.242D500 – 1.256F[i] 500 – 2.307IR[j] 500 + 0.675T | 0.813 | 0.003 | 14.66 | 22.17 |

*Note:* Numbers 500 and 1000 in the equations are related to the radius buffers and not a part of numbers.
[a] Population.
[b] Rainfall.
[c] Elevation.
[d] Urban.
[e] Aridisols.
[f] Inceptisol soils.
[g] Dry farming.
[h] Poor land.
[i] Forest.
[j] Irrigated.
[k] Root mean square error = 1/N $\sqrt{(\text{observed-predicted})^2}$.
[l] Temperature.

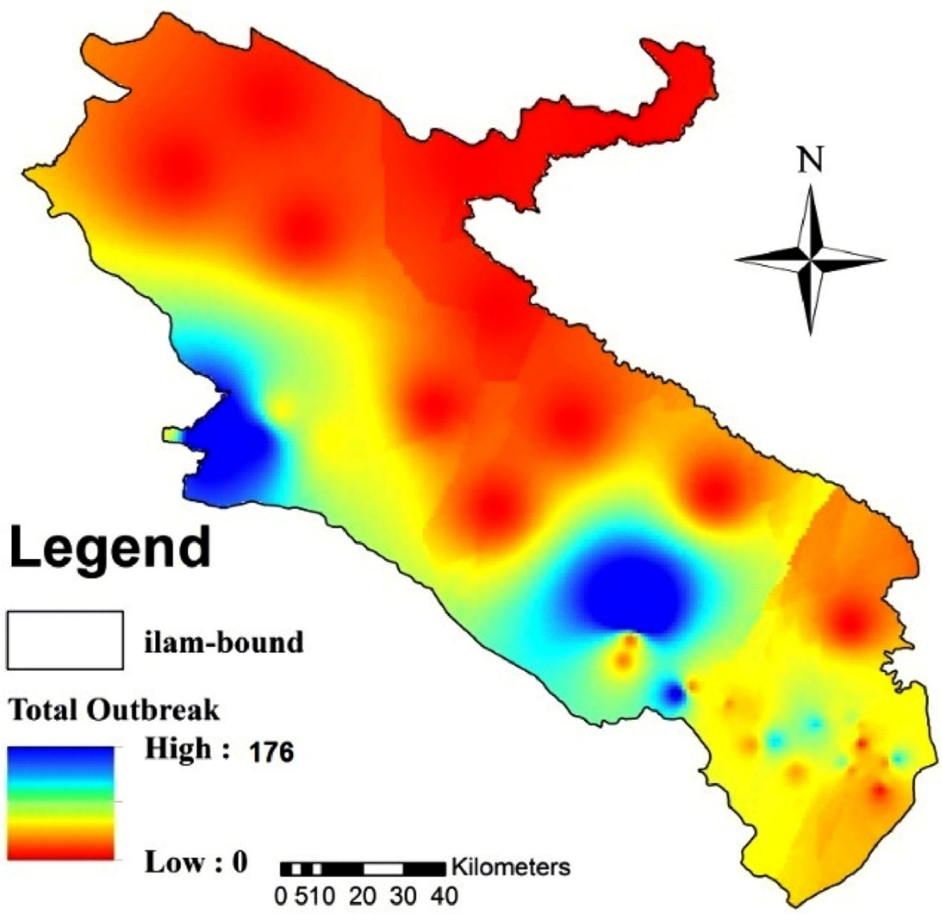


**Fig. 3.** Spatial distribution map of cutaneous leishmaniasis in Ilam Province, western Iran, based on IDW model.

ferent regions of Iran (Ali-Akbarpour et al., 2012; Yoosefi and Vakil, 2007). In another study the same as current research, climate conditions were used to map the prevalence risk of visceral leishmaniasis in Meshkinshahr, Iran, using GIS. Visceral leishmaniasis was significantly accosiated with temperature ($P$ = 0.007), number of days with minus zero temperature ($P$ = 0.009), and humidity ($P$ = 0.001) (Salahi-Moghaddam et al., 2010).

The results of the yearly and the three-year average regression equations (Table 2) showed that the coefficient of the elevation impact on CL prevalence was negative. Investigation of elevation aligned lines in DEM map and its comparison with Figs. 3 and 4

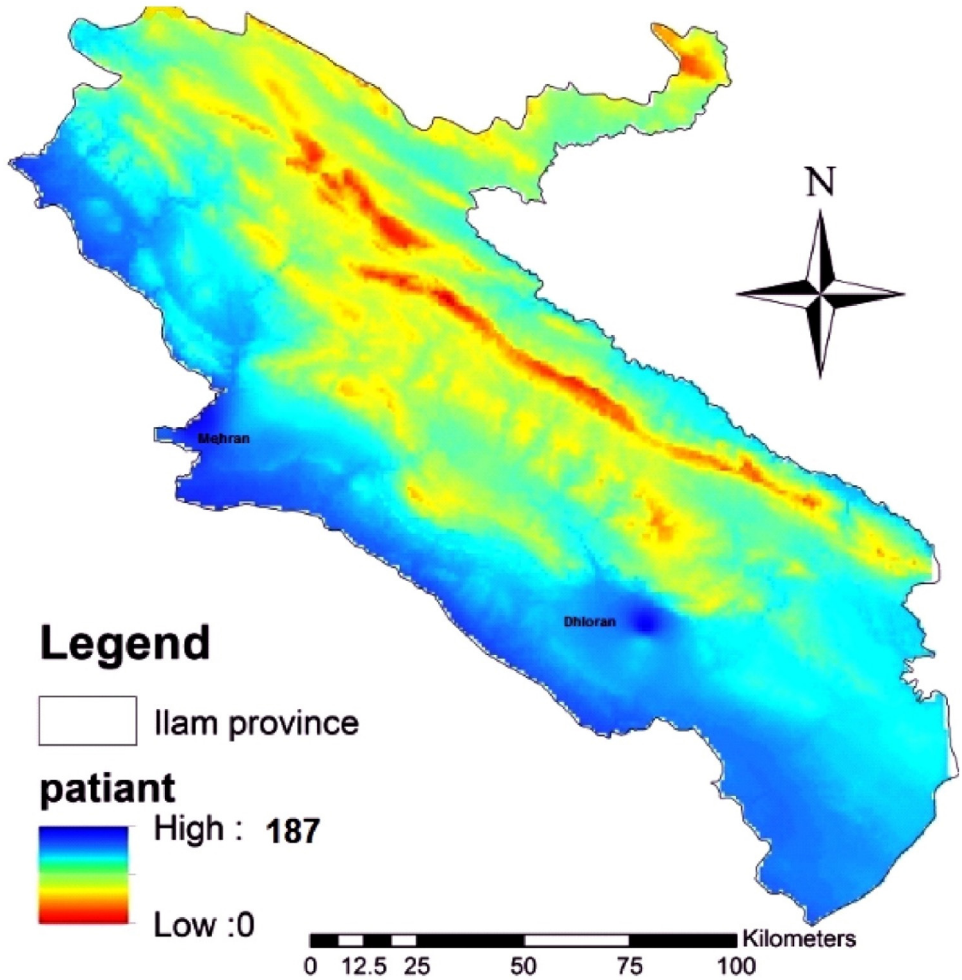


**Fig. 4.** Predictive risk map in different intensities of cutaneous leishmaniasis in Ilam province, western Iran, based on the Land Use Regional models. (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

indicated that approximately all of CL cases occurred in the lowlands with elevation of 100–400 m. In 2013, the coefficient of the elevation in regression equation was 0.0000174 which was lower than other years. For finding the reason, the tables of CL prevalence in 2013 were reexamined and it was observed that higher proportion of infected people in lowland villages was caused the lower coefficient of elevation in regression equation. The coefficient of elevation was not much different in regression equations of 3-year average, 2014, and 2015. The results of this study are supported by previous study in Middle East which showed that CL prevalence hotspots were located in low latitudes areas (Salahuddin M. et al., 2013). Another study about distribution of zoonotic CL in Golestan province, north-east of Iran, has shown that 97.8% of cases were located at low altitudes below 725 m above the sea level (Mollalo et al., 2014).

Since the most of the surface areas within 500 and 1000 m radius of the residential places of the patients were occupied by an urban building, covering soil was not illustrated in land use digital maps, and as a result, the coefficient of covering soil was negative in most of the equations. However, after insecticides spraying and rodents killing in the cities during 2013 by the province Health Center, the more morbidities were reported in marginal settlements or among the nomads living in the countryside where there was non-urban space in 1000 m radius of their habitations. Therefore, in regression equations related to 2013, the positive coefficients of covering soil were found for Inceptisol soils1000 (0.079) and Aridisol soils1000 (0.279). More Leishmaniasis morbidities were observed in marginal settlements with more open spaces and more under construction places. Although being located in the urban area, in fact these areas are occupied by residential, agricultural, and uncultivated spaces and places for demolition and construction waste dumping which is difficult to sort (Nejati et al., 2014; Rostami et al., 2013).

In all of regression equations, among five predictive variables for land use, the greatest positive coefficients were related to the urban land use parameter. For example, it was 10.572 in 3-year average regression equation. This study focused on CL as an infection disease in the urban and rural areas. However, there were some non-residential spaces in marginal settlements which were legally considered as the urban area because of financial limitations for areas sorting. This may be the most probable explanation for high coefficient values related to land use parameter in the regression equations. In order to minimize the calculation error in coefficient of land use, it is better to separate these areas and examine their impacts on LC prevalence individually.

The regression analysis showed that there was an inverse relation between rainfall and CL prevalence. Comparison of CL distribution map (Fig. 3) and predictive risk map (Fig. 4) to isohyet aligned line with rainfall slope indicated that the highest prevalence was found in hot desert areas with annual rainfall of 220 mm. These results are inconsistent with some studies in which more prevalence of visceral leishmaniasis was observed in areas with more rainfall (Elnaiem et al., 2003; Thomson et al., 1999). This

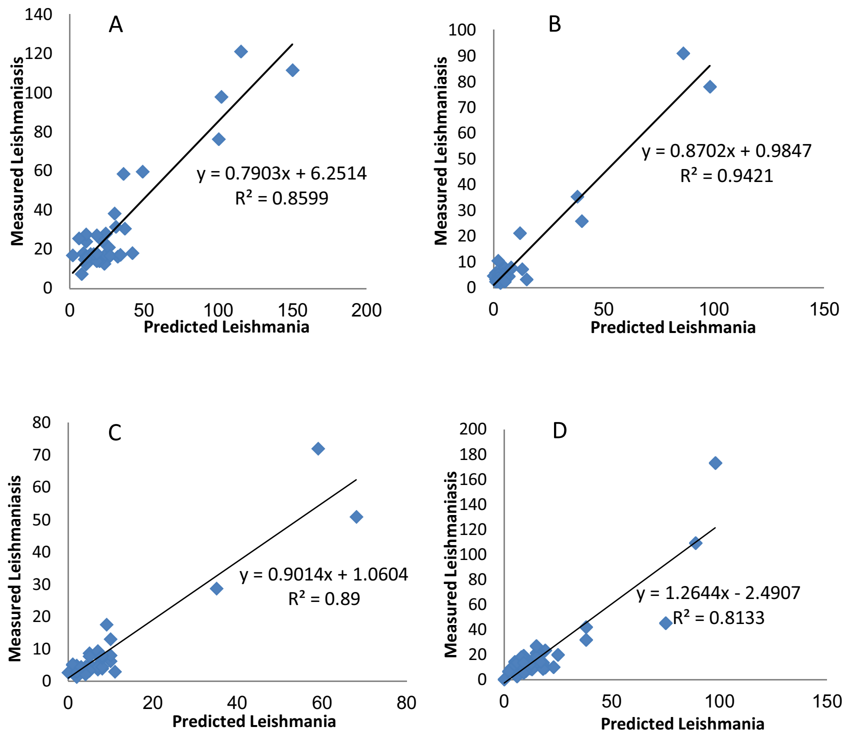


**Fig. 5.** Measured versus predicted response for (A) mean leishmaniasis (B) 2013 leishmaniasis, (C) 2014 leishmaniasis, and (D) 2015 leishmaniasis.

inconsistency can be explained by the fact that in the present study most of the high precipitation areas were located in cold regions with an elevation of more than 700 m where the coldness worked as a preventive factor for CL prevalence.

The coefficient of the population density as a predictive variable for CL prevalence, in spite of its low value was positive in all four equations and it was found to be 0.0000185 in 3-year average regression equation. Low coefficient of population can be explained by the fact that the most of the patients lived in marginal settlements where the density of population was very low.

In 2015, the coefficient of the irrigated agriculture in regression equation was −2.307. In other regression equations, this predictive variable did not has an impact on Cl prevalence. This study revealed that the desolate nest of the rodents are main living places for sand flies.The rodents which live in the desert and agricultural lands, however, rarely return to their old nest after digging a new shelter. Therefore, the sequential plowing of the farm lands can considerably decrease desolate nest and consequently reduce sand flies (Rossi et al., 2007; Wasserberg et al., 2003). An investigation in Tunisia in 2015 demonstrated that the development of the irrigation for agricultural aims in an arid area significantly decreased most species of sand flies and only some species increased (Cortes et al., 2012). Comparing our results with this study suggested that the development of the irrigated agriculture might work as a preventive factor for CL prevalence.

This study was limited by lack of long-term statistics about CL which might affect the results; however, the large number of data (3237 CL patients) can somewhat solve the problem.

Finally, spatial distribution of CL was determined in Ilam province based on IDW method. Spatial maps indicated that the west of Ilam had the highest CL prevalence. LUR model was employed to develop a CL risk map in Ilam, Iran, for the first time. Many environmental variables that can affect on CL prevalence were applied to generate this model. 11 examined environmental variables were found to have statistically significant relationship with CL prevalence ($P$ value $\leq$ 0.05) at least in one of four developed LUR. Based on the developed LUR, lower elevation (low lands), higher temperature, urban use of land, and Inceptisol and Aridisol soils had a positive effect on CL prevalence. Therefore, in the areas with these specifications, the preventive and regulatory actions should be done. The risk map indicates that the eastern areas of Ilam province are in high risk for CL prevalence. The predictive risk map cannot be an alternative for ecological fieldwork and reliable reporting systems; however, it can be a helpful tool to make and design preventive programs by decision makers.

## Acknowledgements

The authors would like to acknowledge the Dean of the School of Health, Shahid Sadoughi University of Medical Sciences for his kindly support. This study was conducted by financial support of the Ilam University of Medical Sciences, Project Number: 910539.

## References

Ali-Akbarpour, M., Mohammadbeigi, A., Tabatabaee, S.H.R., Hatam, G., 2012. Spatial analysis of eco-environmental risk factors of cutaneous leishmaniasis in southern Iran. J. Cutan. Aaesthet. Surg. 5, 30.

Amini, H., Taghavi-Shahri, S.M., Henderson, S.B., Naddafi, K., Nabizadeh, R., Yunesian, M., 2014. Land use regression models to estimate the annual and seasonal spatial variability of sulfur dioxide and particulate matter in Tehran. Iran Sci. Total Environ. 488, 343–353.

Arekhi, S., Heydari, M., Pourbabaei, H., 2010. Vegetation-Environmental Relationships and Ecological Species Groups of the Ilam Oak Forest Landscape, Iran. Caspian J. Env. Sci. 8 (2), 115–125.

Bavia, M., Carneiro, D., da Costa Gurgel, H., Filho, C.M., Barbosa, M.R., 2005. Remote sensing and geographic information systems and risk of American visceral leishmaniasis in Bahia, Brazil. Parassitologia 47, 165.

Ben-Ahmed, K., Aoun, K., Jeddi, F., Ghrab, J., El-Aroui, M.-A., Bouratbine, A., 2009. Visceral leishmaniasis in Tunisia: spatial distribution and association with climatic factors. Am. J. Trop. Med. Hyg. 81, 40–45.

Bhunia, G.S., Kesari, S., Chatterjee, N., Kumar, V., Das, P., 2012. The burden of visceral leishmaniasis in India: challenges in using remote sensing and GIS to understand and control ISRN. Infect. Dis. 2013.

Bhunia, G.S., Kesari, S., Chatterjee, N., Kumar, V., Das, P., 2013. Spatial and temporal variation and hotspot detection of kala-azar disease in Vaishali district (Bihar), India. BMC Infect. Dis. 13, 1.

Chamaillé, L., Tran, A., Meunier, A., Bourdoiseau, G., Ready, P., Dedet, J.-P., 2010. Environmental risk mapping of canine leishmaniasis in France. Parasit. Vectors 3, 5.
Chaves, L.F., Pascual, M., 2006. Climate cycles and forecasts of cutaneous leishmaniasis, a nonstationary vector-borne disease. PLoS Med. 3, e295.
Cortes, S., Vaz, Y., Neves, R., Maia, C., Cardoso, L., Campino, L., 2012. Risk factors for canine leishmaniasis in an endemic Mediterranean region. Vet. Parasitol. 189, 189–196.
Desjeux, P., 2001. The increase in risk factors for leishmaniasis worldwide. Trans. R. Soc. Trop. Med. Hyg. 95, 239–243.
Doudi, M., 2011. The study of genetic polymorphism of leishmania major and leishmania tropica by PCR-RFLP technique in two hyper-endemic regions: Isfahan and Bam. Iran Arak Med. Univ. J. 14, 20–29.
das Chagas Xavier, S.C., Roque, A.L.R., dos Santos Lima, V., Monteiro, K.J.L., Otaviano, J.C.R., da Silva, L.F.C.F., Jansen, A.M., 2012. Lower richness of small wild mammal species and chagas disease risk. PLoS Negl. Trop. Dis. 6, e1647.
Elnaiem, D.-E.A., et al., 2003. Risk mapping of visceral leishmaniasis: the role of local variation in rainfall and altitude on the presence and incidence of kala-azar in eastern Sudan. Am. J. Trop. Med. Hyg. 68, 10–17.
Gumiere, S.J., Lafond, J.A., Hallema, D.W., Périard, Y., Caron, J., Gallichand, J., 2014. Mapping soil hydraulic conductivity and matric potential for water management of cranberry: Characterisation and spatial interpolation methods. Biosyst. Eng. 128, 29–40.
Hanafi-Bojd, A., et al., 2012. Spatial analysis and mapping of malaria risk in an endemic area, south of Iran: a GIS based decision making for planning of control. Acta Trop. 122, 132–137.
Hoek, G., Beelen, R., De Hoogh, K., Vienneau, D., Gulliver, J., Fischer, P., Briggs, D., 2008. A review of land-use regression models to assess spatial variation of outdoor air pollution. Atmos. Environ. 42, 7561–7578.
Karimi, A., Hanafi-Bojed, A., Yaghoobi-Ershadi, M., Akhavan, A., Ghezelbash, Z., 2014. Spatial and temporal distributions of phlebotomine sand flies(Diptera: Psychodidae), vectors of leishmaniasis, in IranAmeneh. Acta Tropica 132, 131–139.
King, R.J., Campbell-Lendrum, D.H., Davies, C.R., 2004. Predicting geographic variation in cutaneous leishmaniasis, Colombia. Emerg. Infect. Dis. 10, 598–607.
Liu, W., et al., 2015. Land use regression models coupled with meteorology to model spatial and temporal variability of NO 2 and PM 10 in Changsha, China. Atmos. Environ. 116, 272–280.
Nejati, J., Mojadam, M., Bojd, H., Ali, A., Keyhani, A., Habibi Nodeh, F., 2014. An epidemiological study of cutaneous leishmaniasis in Andimeshk (2005–2010). Sci. J. Ilam Univ. Med. Sci. 21, 94–101.
Mollalo, A., Alimohammadi, A., Shirzadi, M.R., Malek, R., 2014. Geographic information system-based analysis of the spatial and spatio-temporal distribution of Zoonotic cutaneous leishmaniasis in Golestan Province, North-East of Iran. Zoonoses Public Health 62 (1), 18–28.
Reithinger, R., Dujardin, J.-C., Louzir, H., Pirmez, C., Alexander, B., Brooker, S., 2007. Cutaneous leishmaniasis. Lancet Infect. Dis. 7, 581–596.
Rossi, E., et al., 2007. Mapping the main leishmania phlebotomine vector in the endemic focus of the Mt. Vesuvius in southern Italy. Geospat. Health 1, 191–198.Rostami, M.N., Saghafipour, A., Vesali, E., 2013. A newly emerged cutaneous leishmaniasis focus in central, Iran. Int. J. Infect. Dis. 17, e1198–e1206.
Ryan, J.R., et al., 2006. Spatial clustering and epidemiological aspects of visceral leishmaniasis in two endemic villages, Baringo District, Kenya. Am. J. Trop. Med. Hyg. 74, 308–317.
Sabaliauskas, K., Jeong, C.-H., Yao, X., Reali, C., Sun, T., Evans, G.J., 2015. Development of a land-use regression model for ultrafine particles in Toronto, Canada. Atmos. Environ. 110, 84–92.
Salah, A.B., Kamarianakis, Y., Chlif, S., Alaya, N.B., Prastacos, P., 2007. Zoonotic cutaneous leishmaniasis in central Tunisia: spatio-temporal dynamics. Int. J. Epidemiol. 36, 991–1000.
Salahi-Moghaddam, A., Mohebali Mehdi, M., Ali, M., Habibi Majid, M., Zarei Zabiholah, Z., 2010. Ecological study and risk mapping of visceral leishmaniasis in an endemic area of Iran based on a geographical information systems approach. Geospat. Health 5 (1), pp. 71–77.
Salahi-Moghaddam, A., Khoshdel, A., Hanafi-Bojd, A.-A., Sedaghat, M.-M., 2015. Mapping and review of leishmaniasis, its vectors and main reservoirs in Iran. J. Kerman Univ. Med. Sci. 22, 83–104.
Jaber, Salahuddin M., Ibbini, Jwan H., Hijjawi, Nawal S., Amdar, Nafn M., Huwail, Mohammed J., Al-Aboud, Khalid, 2013. Exploring recent spatial patterns of cutaneous leishmaniasis and their associations with climate in some countries of the Middle East using geographical information systems. Geospatial Health 8 (1), 143–158.
Shirzadi, M.R., Mollalo, A., Yaghoobi-Ershadi, M.R., 2015. Dynamic relations between incidence of zoonotic cutaneous leishmaniasis and climatic factors in Golestan Province, Iran. J. Arthropod-Borne Dis. 9, 148.
Sudhakar, S., Srinivas, T., Palit, A., Kar, S., Battacharya, S., 2006. Mapping of risk prone areas of kala-azar (Visceral leishmaniasis) in parts of Bihar state, India: an RS and GIS approach. J. Vector Borne Dis. 43, 115.
Thomson, M., Elnaiern, D., Ashford, R., Connor, S., 1999. Towards a kala azar risk map for Sudan: mapping the potential distribution of phlebotomus orientalis using digital data of environmental variables. Trop. Med. Int. Health 4, 105–113.
Wasserberg, G., Abramsky, Z., Kotler, B., Ostfeld, R., Yarom, I., Warburg, A., 2003. Anthropogenic disturbances enhance occurrence of cutaneous leishmaniasis in Israel deserts: patterns and mechanisms. Ecol. Appl. 13, 868–881.
Webster, R., Oliver, M.A., 2007. Geostatistics for Environmental Scientists. John Wiley & Sons.
Weigle, K.A., Santrich, C., Martinez, F., Valderrama, L., Saravia, N.G., 1993. Epidemiology of cutaneous leishmaniasis in Colombia: environmental and behavioral risk factors for infection, clinical manifestations, and pathogenicity. J. Infect. Dis. 168, 709–714.
Yoosefi, H., Vakil, N., 2007. A survey about the effect of immune response raised by leishmania major on fibrosarcoma tumor in Balb/c mice. Arak Med. Univ. J. 10, 81–86.